Sleep: Model Reduction in Deep Active Inference

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Abstract. Sleep is one of the most important states of the human mind and body. Sleep has various functions, such as restoration, both physically and mentally, and memory processing. The theory of active inference frames sleep as the minimization of complexity and free energy in the absence of sensory information. In this paper, we propose a method for model reduction of neural networks that implement the active inference framework. The proposed method suggests initializing the network with a high latent space dimensionality and pruning dimensions subsequently. We show that reduction of latent space dimensionality decreases complexity without increasing free energy.

Keywords: Active inference · Model reduction · Sleep

1 Introduction

Sleep is a phenomenon that occurs in most animals [10]. It is a topic of intensive research as it has been shown to be important for both the mind [18,12] and the body [14]. In particular, sleep and learning have been connected in many hypotheses [17,3], as well as mental health [4] and memory [20].

Active inference is a theory of behaviour and learning that originated in neuroscience [8]. The basic assumption is that intelligent agents attempt to minimize their variational free energy. Variational free energy — named for its counterpart in statistical physics i.e. Helmholtz free energy — is also known as the evidence lower bound (ELBO) in variational Bayesian methods.

Since its conception, active inference has been explored in multiple subfields of neuroscience and biology [6,5,11] and eventually found its way into the field of computer science [19,15,2]. In particular, Ueltzhöffer [19] and Çatal *et al.* [2] have made developments in *deep active inference*, i.e. the use of deep neural networks to implement active inference.

Recent work [13,9,7] has pointed out the relation between the function of removing redundant connections during sleep and Bayesian model reduction (BMR) in active inference, i.e. complexity minimization through elimination of redundant parameters. In this work, we propose a method for reducing complexity in the deep active inference framework. We evaluate the method through simulation experiments.

2 Deep active inference

Currently, using deep neural networks in active inference to learn state spaces, in addition to policy and posterior, is becoming increasingly popular, which contrasts with active inference on discrete state spaces as described in [9]. In this approach, the dimensionality of the state space is a hyperparameter, i.e. it must be specified before training and cannot change along the way. Here, we briefly introduce the method provided by Çatal *et al.* [2].

Assuming the policy π may be broken up into a sequence of actions $\mathbf{a}_t$ and the current state depends on the previous action instead of the policy, a generative model with observations $\mathbf{o}_t$ and states $\mathbf{s}_t$ is defined as

$$P(\tilde{\mathbf{o}}, \tilde{\mathbf{s}}, \tilde{\mathbf{a}}) = P(\mathbf{s}_0)P(\tilde{\mathbf{a}}) \prod_{t=1}^{T} P(\mathbf{o}_t|\mathbf{s}_t)P(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{a}_{t-1}), \tag{1}$$

where $\tilde{\mathbf{x}} = (\mathbf{x}_0, \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T)$.

Deep neural networks are used to parameterize the prior, likelihood and approximate posterior distributions: $p_\theta(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{a}_{t-1})$, $p_\phi(\mathbf{o}_t|\mathbf{s}_t)$ and $q_\xi(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{a}_{t-1}, \mathbf{o}_t)$, respectively. With this, minimization of free energy consists of minimizing the loss function

$$\begin{aligned} &L(\theta, \phi, \xi; \mathbf{o}_t, \mathbf{s}_{t-1}, \mathbf{a}_{t-1}) = \\ &\qquad D_{\mathrm{KL}}(q_\xi(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{a}_{t-1}, \mathbf{o}_t)||p_\theta(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{a}_{t-1})) - \log p_\phi(\mathbf{o}_t|\mathbf{s}_t). \end{aligned} \tag{2}$$

Prior, likelihood and posterior distributions are chosen to be multivariate normal distributions. As opposed to the standard VAE, optimization is done over

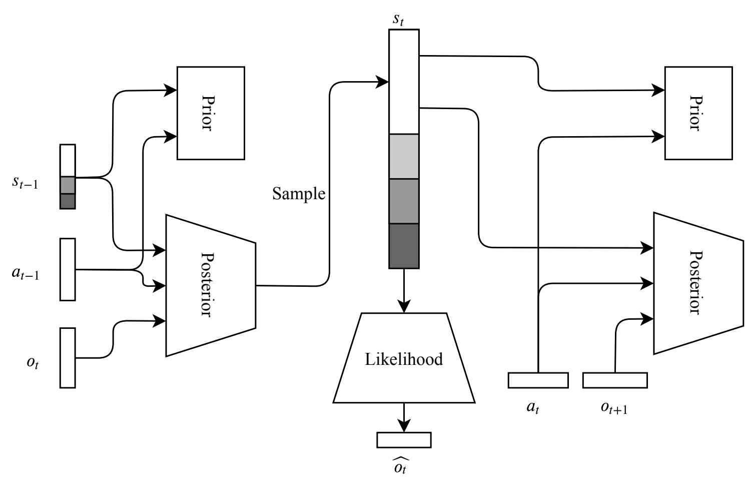

Fig. 1. Information flow of neural networks. The posterior network takes in previous state and action, and current observation. The prior network takes in previous state and action. The likelihood network takes in current state. The state s_t illustrates that dimensions may be pruned, if they are unused.

sequences in time. Additionally, empirical priors are learned, instead of using fixed priors. A chart on the information flow can be found in Figure 1.

3 Latent space dimensionality reduction and sleep

The size of the latent space vector $\mathbf{s}$ is an important hyperparameter. On the one hand, this must be large enough to explain observations in the generative model. On the other hand, it must be kept minimal to reduce complexity as to minimize the required resources, such as memory and power (both computational and electrical). In general, one does not know the optimal size of $\mathbf{s}$. A typical way of finding a well-performing value is a hyperparameter sweep. Parameter sweeps, however, are resource intensive and require many unnecessary training runs. Therefore, we propose a method for dimensionality reduction in the deep active inference framework.

The basic idea is to prune dimensions in the latent space vector $\mathbf{s}$. A popular method for inspecting informative dimensions of a vector space is singular value decomposition (SVD). This technique is used to factorize an $m \times n$ matrix $\boldsymbol{A}$ into three matrices $\boldsymbol{USV}^*$, where a common geometrical interpretation is that the decomposition gives 2 rotation matrices $\boldsymbol{U}$ and $\boldsymbol{V}^*$, and a scaling matrix $\boldsymbol{S}$.

Algorithm 1 lines out the method in the form of pseudo-code. Let n be the dimensionality of the latent space. We sample a latent space vector from m different sequences to construct the column vectors of a matrix $\boldsymbol{A}$. The column space of $\boldsymbol{A}$, denoted $\mathcal{C}(\boldsymbol{A})$, forms a subspace of the latent space. Applying SVD to $\boldsymbol{A}$ gives the scaling matrix $\boldsymbol{S}$. The values on the diagonal of $\boldsymbol{S}$ are the singular values of $\boldsymbol{A}$, and suggest a size for the dimensions of $\mathcal{C}(\boldsymbol{A})$ after rotation with $\boldsymbol{U}$. Dimensions with small singular values are assumed to be unused. To this

Algorithm 1: Sleep

```
input  : A trained model model with dimensionality n
         The number of repetitions N and number of sequences m
         A threshold α
output : The new latent space dimensionality ν
while i < N do
    A ← []                                          // make a matrix
    while j < m do
        a ← GenerateSequence(model)                 // generate a new sequence
        v ← Sample(a)                               // sample a latent space vector
        A ← [A, v]                                  // insert vector as a new column in matrix
        j ← j + 1
    S ← SVD(A)                                      // apply SVD to matrix
    c_i ← #(S_kk > α) for 0 < k < n                 // count sv's over threshold
    c ← [c, c_i]                                    // add number to list of outcomes
    i ← i + 1
ν ← Avg(c)                                          // average over all outcomes
```

end, we define a threshold α for which dimensions corresponding to singular values smaller than α can be pruned. We repeat this procedure N times — by generating m new sequences each time — and average the number of pruned dimensions, in order to obtain a relatively robust outcome.

It is important to stress, here, that SVD does not allow one to find *which* dimensions can be pruned. Instead, it is used to converge to the optimal *number* of dimensions. SVD provides the size of dimensions of the column space of $\boldsymbol{A}$, i.e. $\mathcal{C}(\boldsymbol{A})$, described in a basis of the latent space after a rotation with $\boldsymbol{U}$. The actual basis vectors are a linear combination of the rotated basis vectors. In other words, having a zero dimension in rotated latent space, does not necessarily mean there is one in latent space. However, it does indicate that it is possible to reduce dimensionality by choosing a different rotation, since it shows that there is an orientation of the basis vectors which requires less dimensions to describe the column space. Returning to the model, by retraining with a lower dimensionality n, we essentially force the model to learn the latent space with a different orientation which requires less dimensions.

We have dubbed the method *sleep*, since it replicates synapse pruning, as well as Bayesian model reduction. From an active inference perspective, the proposed method is analogous to BMR in that it considers a generative model with a large number of latent factors and optimizes this number post hoc [16]. In other words, both the goals of the proposed method and BMR are to consider alternative models which may give simpler explanations for the same observations. That said, in both cases, the balance between accuracy and complexity is crucial, i.e. accuracy should not suffer due to simplicity. Indeed, the measure for this trade-off is free energy.

Since latent space in deep active inference is learned using deep neural networks, there is no guarantee that each latent space dimension represents an individual feature. Without knowing what is contained in latent space, it is not possible to target specific parameters to turn off as in BMR. Because of this, algorithm 1 must be succeeded by retraining to obtain a reduced model. In this sense, the earlier analogy is incomplete, since BMR allows one to obtain the reduced model parameters from the full model, i.e. it allows one to find *which* dimensions can be pruned.

In the end, the purpose of the sleep method is to reduce complexity whenever an application (e.g. a robot running a deep active inference implementation) has downtime. The overall sequence of events, then, proceeds as follows. Start with a large value for the latent space dimensionality and train the model. Deploy the model on the application. Each time there is downtime in the application (e.g. the robot is charging), reduce the model by sleeping and retraining. Continue this pattern of sleeping and retraining until the model cannot reduce any further.

4 Experimental setup

Experiments were performed using two environments from the OpenAI Gym [1]. The first experiment employs a modified version of the MountainCar environment, where noise is added to the observation and only the position can be observed. The goal of this environment is to drive up a steep mountain using an underpowered car that starts in a valley. The car is underpowered in the sense that it cannot produce enough force to go against gravity and drive up the mountain in one go. It must first build up enough momentum by driving up the side(s) of the valley. In this experiment, we know upfront that the model only needs 2 dimensions in latent space: position and velocity. Details about the neural networks used for this experiment can be found in Appendix 2.1.

The second experiment employs the CarRacing environment. The goal of this environment is to stay in the middle of a race track using a race car. The car and track are viewed from a top-down perspective. The car must steer left and right to stay on track. Compared to the MountainCar, the CarRacing environment utilizes more complicated dynamics and produces higher dimensional observations. Examples of the environments can be found in Appendix 1. Details about the neural networks used for this experiment can be found in Appendix 2.2.

5 Results

Fig. 2 shows the evolution of the free energy of MountainCar during training with a fixed number of latent space dimensions (see Appendix 3.1 for a similar figure for CarRacing). It suggests that free energy decreases as more state space dimensions are added. However, it also shows that free energy does not visibly decrease beyond a certain number of dimensions. For the MountainCar, we see that the free energy does not decrease for more than 2 dimensions, while for the CarRacing (Appendix 3.1), we see that the free energy does not decrease for more than 4 dimensions. In essence, there appears to be a critical value of the latent space size. For latent spaces larger than this critical value, the free energy does not reduce. This critical value corresponds to the optimal value for the dimensionality with respect to the accuracy/complexity trade-off.

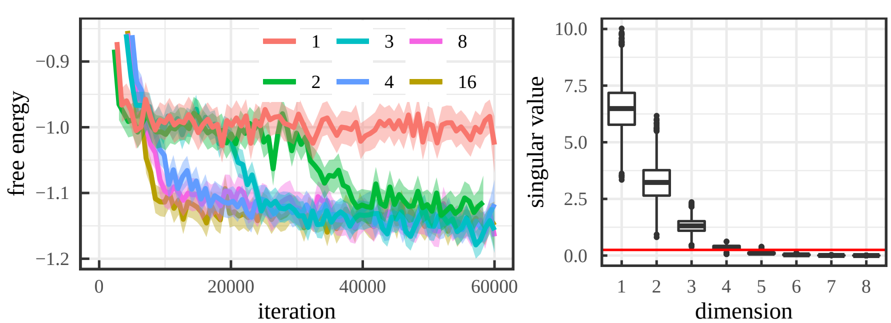

Fig. 2. (Left) Free energy during training of MountainCar for different state space sizes. Curves show smoothed data (LOESS, span 0.02) with 95% standard error bands. (Right) Boxplot of singular values while sleeping at 8 latent space dimensions ($N = 10^4$).

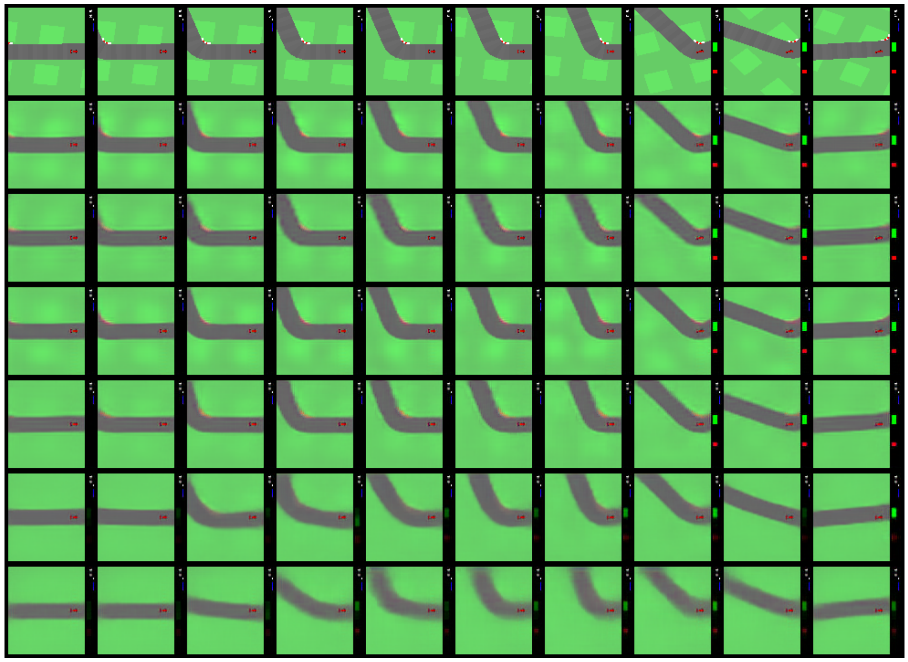

Fig. 3. Reconstructions of CarRacing track over time with different latent space dimensions. From top to bottom: ground truth, 32, 16, 8, 4, 2, 1.

Fig. 3 demonstrates how latent space dimensionality affects reconstruction and how too few dimensions can lead to aspects of the environment not being learned. It shows reconstructions of the CarRacing track for latent space dimensions of 32, 16, 8, 4, 2 and 1 (top to bottom with ground truth in the top sequence). Note how the curvature of the track is not accurately reconstructed through 1 dimension, especially at early time steps. Also, 2 dimensions still seem to lack accuracy (see curvature in second time step). Furthermore, note how the feedback bar is incorrectly encoded by dimensions lower than 4.

Fig. 2 also shows a boxplot for the singular values obtained for the MountainCar with 8 latent space dimensions for $N = 10^4$ iterations (plots for different latent space dimensions can be found in Appendix 3.2). The red line shows a threshold $\alpha = 0.25$. The figure suggests that there is a difference in sizes in the latent space dimensions. Indeed, the first four singular values are on average larger than α, while the remaining values are on average smaller than α. This indicates that certain dimensions are very small, therefore, contain less information, and may be pruned subsequently.

Fig. 4 illustrates the algorithm put into practice with different sleep cycles for the CarRacer with threshold set at $\alpha = 0.25$, where we started with 16 latent space dimensions. In this example, we initiated sleep every 5×10^4 training iterations and checked if dimensionality could be reduced. If so, we pruned and

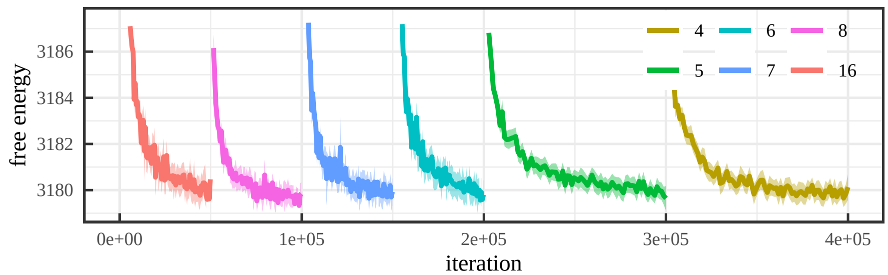

Fig. 4. Free energy over 7 sleep cycles of CarRacer. Setting threshold $\alpha = 0.25$ gives the reduction: $16 \rightarrow 8 \rightarrow 7 \rightarrow 6 \rightarrow 5 \rightarrow 4$, after which it cannot reduce further. Curves show smoothed data (LOESS, span 0.02) with 95% standard error bands.

restarted training with lower dimensionality, else we continued training for 5×10^4 iterations, until reduction was possible. We stopped the process after 7 sleep cycles. As expected, the sleep sequence manages to reduce the complexity of the model, without impacting the free energy negatively.

When compared to Fig. 8 in Appendix 3.2, the previous result is exactly as expected. Following the steps described there, the state space can effectively be pruned down to 4 dimensions. Observe that if we were to repeat the experiment for the MountainCar, Fig. 7 in Appendix 3.2 shows that setting the threshold at $\alpha = 0.25$ would return a state space dimensionality of 2.

6 Conclusion

Our results show that it is possible to train a deep active inference model by setting a large number of latent space dimensions and subsequently sleeping until minimal complexity is reached. However, the method proposed in this paper is not optimal. A few caveats remain. First of all, the current method requires retraining. After applying SVD, the entire model must be retrained from scratch. Second of all, there exist limitations to SVD. For instance, SVD does not take into account nonlinear transformations. Therefore, relations between different dimensions may remain and the optimal dimensionality may never be reached.

In future work, we will investigate the effects of sleeping at regular intervals during training. For example, we may sleep after every 10^4 time steps to check if we can already reduce the latent space. Another option we will investigate, is to prune both unnecessary dimensions and weights. This way, we may be able to maintain the trained neural network, while reducing complexity. In addition, we want to experiment with different methods for dimensionality reduction, such as nonlinear methods. Another option to be explored is to learn and set unused dimensions to 0 during training.

Acknowledgments

This research received funding from the Flemish Government under the "Onderzoeksprogramma Artificiële Intelligentie (AI) Vlaanderen" programme.

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Appendix 1 OpenAI Gym examples

Fig. 5 shows snapshots of the MountainCar and CarRacing environments from the OpenAI Gym [1]. Note that observations in the MountainCar environment consist of position and velocity values, while CarRacing provides RGB pixels.

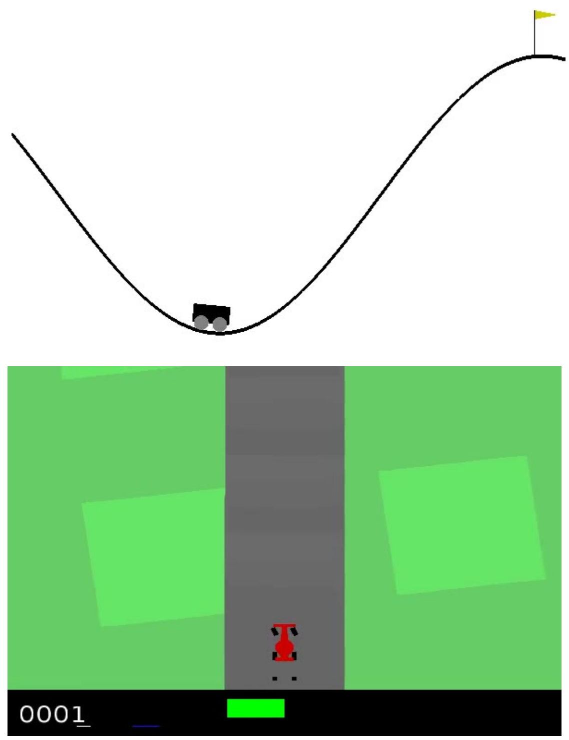

Fig. 5. (Top) Example of MountainCar environment [1]. (Bottom) Example of CarRacing environment [1].

Appendix 2 Neural network definitions

Appendix 2.1 Mountain car

Table 1 shows the neural architecture of the network used in the MountainCar experiments.

Table 1. Specifications of the MountainCar neural network with s latent space dimensions.

	Layer	Neurons/Filters	Activation Function
Posterior	Linear	20	Leaky ReLU
	Linear	$2 \times s$	Leaku ReLU
Likelihood	Linear	20	Leaky ReLU
	Linear	2	Leaky ReLU
Prior	Linear	20	Leaky ReLU
	Linear	$2 \times s$	Leaky ReLU

Appendix 2.2 Car racing

Table 2 shows the neural architecture of the network used in the CarRacing experiments. All filters have 3×3 kernel, as well as stride and padding of 1.

Table 2. Specifications of the CarRacing neural network with s latent space dimensions.

	Layer	Neurons/Filters	Activation Function
Posterior	Convolutional	8	Leaky ReLU
	Convolutional	16	Leaky ReLU
	Convolutional	32	Leaky ReLU
	Convolutional	64	Leaky ReLU
	Convolutional	128	Leaky ReLU
	Convolutional	256	Leaky ReLU
	concat	N/A	N/A
	Linear	$2 \times s$	Leaku ReLU
Likelihood	Linear	$128 \times 2 \times 9$	Leaky ReLU
	Convolutional	128	Leaky ReLU
	Convolutional	64	Leaky ReLU
	Convolutional	32	Leaky ReLU
	Convolutional	16	Leaky ReLU
	Convolutional	8	Leaky ReLU
	Convolutional	3	Leaky ReLU
Prior	LSTM cell	128	Leaky ReLU
	Linear	$2 \times s$	Softplus

Appendix 3 Additional plots

Appendix 3.1 Free energy during training

Fig. 6 shows the evolution of the free energy during training for CarRacing similar to the left plot in Fig. 2. Note how the free energy does not visibly decrease when using more than 4 dimensions.

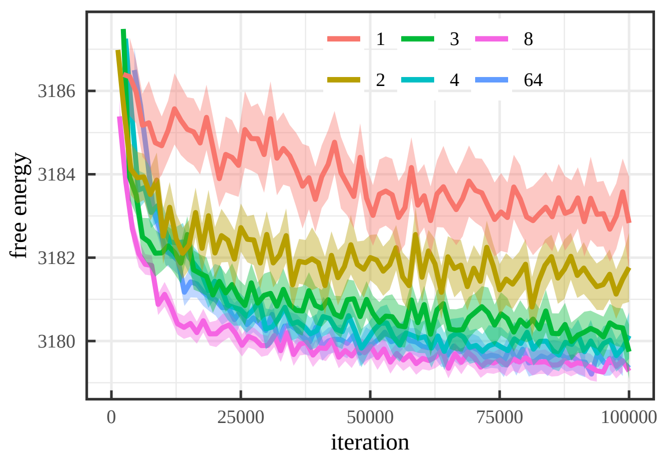

Fig. 6. Free energy during training of CarRacer for different state space sizes. Curves show smoothed data (LOESS, span 0.02) with 95% standard error bands.

Appendix 3.2 Boxplots for different latent space dimensions

Fig. 7 shows boxplots for the singular values obtained for the MountainCar with different latent space dimensions for 10^4 iterations, while Fig. 8 shows the same for the CarRacing. The red line in each plot indicates the threshold $\alpha = 0.25$.

One can do the following mental exercise. Choose a boxplot and count the amount of dimensions that are above threshold on average. This number will be the new dimensionality. Go to the boxplot for that dimensionality and, again, count the amount of dimensions. Repeat this until the dimensionality does not reduce further. Using this process, we can see that the MountainCar will not reduce below 2 and the CarRacing will not reduce below 4.

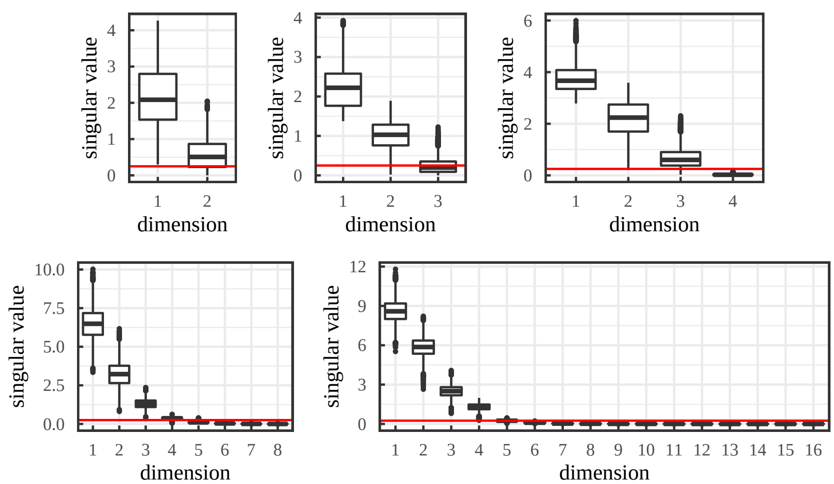

Fig. 7. Boxplots of singular values while sleeping at different latent space dimensions for the MountainCar ($N = 10^4$).

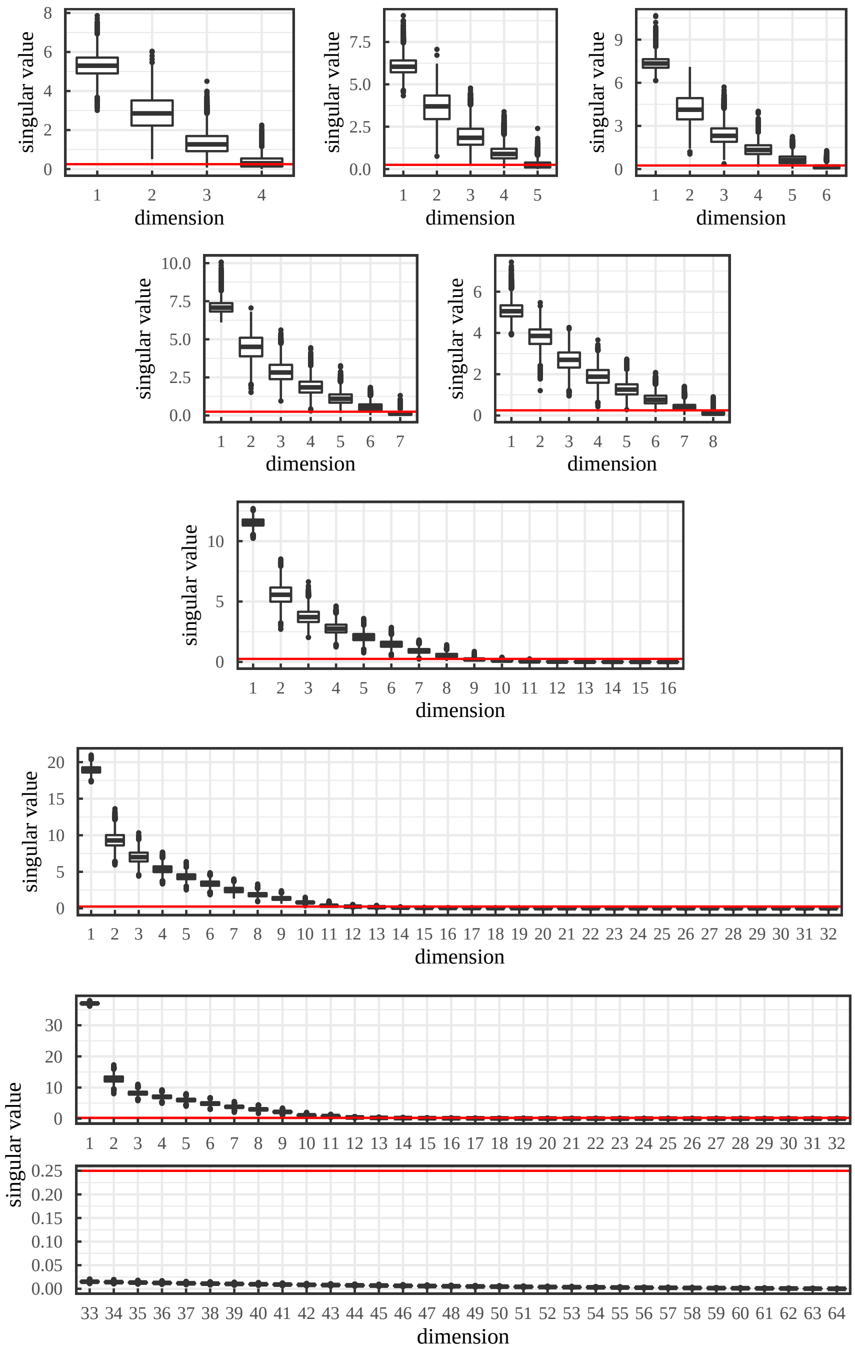

Fig. 8. Boxplots of singular values while sleeping at different latent space dimensions for the CarRacing ($N = 10^4$).

IWAI 2020

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The 1st International Workshop on Active Inference wants to bring together researchers on active inference as well as related research fields in order to discuss current trends, novel results, (real-world) applications, to what extent active inference can be used in modern machine learning settings, such as deep learning, and how it can be unified with the latest psychological and neurological insights.

Active inference is a theory of behaviour and learning that originated in neuroscience (Friston et al., 2006). The basic assumption is that intelligent agents entertain a generative model of their environment, and their main goal is to minimize surprise or, more formally, their free energy. The agents do so either by updating their generative model, so that it becomes better at explaining observations (i.e. learning), or by selecting policies that will resolve their surprise (i.e. acting), for example by moving towards prior, preferred states, or by moving towards less ambiguous states (Friston et al., 2017).

In the field of machine learning, the definition of free energy is also known as the (negative) evidence lower bound (ELBO) in variational Bayesian methods. In deep learning, this has become a popular method to build generative models of complex data using the variational autoencoder framework (Kingma et al., 2014, Rezende et al., 2014). Also, active inference has connections with the currently popular domain of reinforcement learning and intrinsic motivation (Friston et al., 2009).

Programme

Invited talks

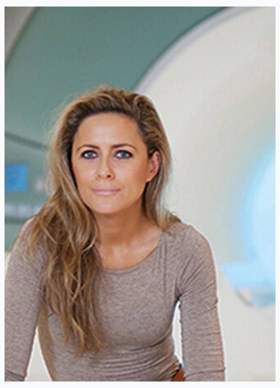
Active Learning and Active Inference in Exploration
Philipp Schwartenbeck

Successful behaviour depends on the right balance between maximising reward and soliciting information about the world. I will discuss how different types of information-gain emerge when casting behaviour as surprise minimisation and planning as an inferential process. This formulation provides two distinct mechanisms for goal-directed exploration that express separable profiles of active sampling to reduce uncertainty. 'Hidden state' exploration motivates agents to sample unambiguous observations to accurately infer the (hidden) state of the world. Conversely, 'model parameter' exploration, compels agents to sample outcomes associated with high uncertainty, if they are informative for their representation of the task structure. I will try to provide an

introductory illustration of the emergence of these types of 'Bayes-optimal' exploratory behaviour, termed active inference and active learning, and discuss possible future developments and experimental investigations of such implementations in artificial and biological agents.
[Presentation]

Putting An End to End-to-End: Gradient-Isolated Learning of Representations
Sindy Löwe

We propose a novel deep learning method for local self-supervised representation learning that does not require labels nor end-to-end backpropagation but exploits the natural order in data instead. Inspired by the observation that biological neural networks appear to learn without backpropagating a global error signal, we split a deep neural network into a stack of gradient-isolated modules. Each module is trained to maximally preserve the information of its inputs using the InfoNCE bound from Oord et al. [2018]. Despite this greedy training, we demonstrate that each module improves upon the output of its predecessor, and that the representations created by the top module yield highly competitive results on downstream classification tasks in the audio and visual domain. The proposal enables optimizing modules asynchronously, allowing large-scale distributed training of very deep neural networks on unlabelled datasets.
[Presentation]



The Free Energy Principle and Active Inference in silico and in vivo, visual sampling and 'world model' building
Rosalyn Moran

The theory of Active Inference proposes that all biological agents retain self-ness by minimizing their long-term average surprisal. In information theoretic terms, Free Energy provides a soluble approximation to this long-term surprise 'now' and necessitates the development of a generative model of the environment within the agent itself. The minimization of this quantity via a gradient flow is purported to be the purpose of neuronal activity in the brain and thus provides a mapping from brain activity to their first-principle computations. In this talk I will outline the theory of Active Inference and describe how discrete and continuous-time systems that perceive and act can be built in silico, while providing evidence for these implementations in neurobiological and behavioral recordings. Using two experiments in human participants, I aim to demonstrate that human visual search and classification of the MNIST dataset (experiment 1) and world model building and adjustment in a maze task (experiment 2) can be cast as Active Inference processes that utilize neurobiologically plausible architectures comprising prediction in visual hierarchies and alterations in precision via neuromodulation.
[Presentation]

Accepted presentations

Confirmatory evidence that healthy individuals can adaptively adjust prior expectations and interoceptive precision estimates
Ryan Smith, Rayus Kuplicki, Adam Teed, Valerie Upshaw and Sahib S. Khalsa
[Presentation]

On the relationship between active inference and control as inference
Beren Millidge, Alexander Tschantz, Anil Seth and Christopher L. Buckley
[Presentation]

Visual search as active inference
Emmanuel Daucé and Laurent Perrinet.
[Presentation]

Integrated World Modeling Theory (IWMT): Towards understanding consciousness by using the Free Energy Principle and Active Inference (FEP-AI) framework to combine Integrated Information Theory (IIT) and Global Neuronal Workspace Theory (GNWT)
Adam Safron
[Presentation]

A deep active inference model of the rubber-hand illusion
Thomas Rood, Marcel van Gerven and Pablo Lanillos
[Presentation]

Sleep: Model Reduction in Deep Active Inference
Samuel Wauthier, Ozan Catal, Cedric De Boom, Tim Verbelen and Bart Dhoedt
[Presentation]

Active Inference for Fault Tolerant Control of Robot Manipulators with Sensory Faults
Corrado Pezzato, Mohamed Baioumy, Carlos Hernandez Corbato, Nick Hawes, Martijn Wisse and Riccardo Ferrari
[Presentation]

Modulation of viability signals for self-regulatory control
Alvaro Ovalle and Simon Lucas
[Presentation]

Active Inference or Control as Inference? A Unifying View
Abraham Imohiosen, Joe Watson and Jan Peters
[Presentation]

A Worked Example of Fokker-Planck based Active Inference
Magnus T. Koudahl and Bert de Vries
[Presentation]

You Only Look... as much as you have to: Using the Free Energy Principle for Active Vision
Toon Van de Maele, Tim Verbelen, Ozan Catal, Cedric De Boom and Bart Dhoedt
[Presentation]

Bayesian hyperparameter dynamics in a Markov chain
Martin Biehl and Ryota Kanai
[Presentation]

Deep active inference for Partially Observable MDPs
Otto van der Himst and Pablo Lanillos
[Presentation]

Accepted posters

Online system identification in a Duffing oscillator by free energy minimisation
Wouter Kouw
[Presentation] [Poster]

Causal blankets: Theory and algorithmic framework
Fernando E. Rosas, Pedro A.M. Mediano, Martin Biehl, Shamil Chandaria and Daniel Polani
[Presentation]

Sophisticated Affective Inference: Simulating Affective Dynamics Induced by Imagined Future Events
Casper Hesp, Alexander Tschantz, Beren Millidge, Maxwell Ramstead, Karl Friston and Ryan Smith
[Presentation]

Learning Where to Park
Burak Ergul, Thijs van de Laar, Magnus Koudahl, Martin Roa Villescas and Bert de Vries
[Presentation]

End-Effect Exploration Drive for Effective Motor Learning
Emmanuel Daucé.
[Presentation]

Hierarchical Gaussian filtering of sufficient statistic time series for active inference
Christoph Mathys and Lilian A.E. Weber
[Presentation]

Call for papers

Papers on all subjects and applications of active inference and related research areas are welcome. Topics of interest include (but are not limited to):

- Active inference
- (Bayesian) surprise
- Cognitive robotics
- Computational neuroscience
- (Deep) generative models
- State space models
- Intrinsic motivation
- Intelligent systems
- ...

Important dates

Abstract Submission Deadline: June 9, 2020
Paper Submission Deadline: ~~June 22, 2020~~ June 28, 2020
Acceptance Notification: ~~July 9, 2020~~ July 15, 2020
Camera Ready Submission Deadline: September 1, 2020
Workshop Date: September 14, 2020

Paper submissions

We welcome submissions of papers with up to 6 printed pages (including references) in LNCS format (click here for details). Submissions will be evaluated according to their originality and relevance to the workshop, and should an abstract of 60-100 words. Contributions should be in PDF format and submitted via Easychair (click here).

In accordance with the main conference, will apply a **double-blind** review process (see also the double-blind reviewing process section below for further details). All papers need to be anonymized in the best of efforts. It is allowed to have a (non-anonymous) online pre-print. Reviewers will be asked not to search for them.

Registration

The workshop registrations will be handled by ECML/PKDD 2020 (click here). At least one author of each accepted paper should register for the conference.

Keep in mind: the early registration deadline for ECML/PKDD is July 20, 2020.

Organisers

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Cedric De Boom, Ghent University - imec, Belgium
Pablo Lanillos, Donders Institute for Brain, Cognition and Behaviour, Netherlands
Christopher Buckley, University of Sussex, United Kingdom

Programme committee

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References

Karl Friston, James Kilner, Lee Harrison. A free energy principle for the brain. Journal of Physiology-Paris, Volume 100, Issues 1–3, 2006.

Karl J. Friston, Jean Daunizeau, and Stefan J. Kiebel. Reinforcement Learning or Active Inference? PLoS ONE, 4(7), 2009.

Karl J. Friston, Marco Lin, Christopher D. Frith, Giovanni Pezzulo, J. Allan Hobson, and Sasha Ondobaka. Active Inference, Curiosity and Insight. Neural Computation, 29(10): 2633–2683, 2017.

Diederik P. Kingma and Max Welling. Auto-encoding variational bayes. 2nd International Conference on Learning Representations, 2014.

Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. 2014. Stochastic backpropagation and approximate inference in deep generative models. 31st International Conference on International Conference on Machine Learning, 2014.